Locally based kernel PLS de-noising with application to event-related potentials

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Abstract

We present a novel signal de-noising algorithm for recovery of signals corrupted by a high levels of noise and applicable in the situations of low sampling rates. This method uses a modification of kernel partial least squares regression (KPLS) defined in reproducing kernel Hilbert space [1]. We treat signal de-noising as a regression problem, in which de-noising consists of estimation of functions which describe a relationship between a set of inputs and dependent outputs corrupted by noise. In signal processing desired functions (signals) are usually assumed to be a linear combination of the basis functions $\phi_i(\mathbf{x})$; i.e. : $f(\mathbf{x}) = \sum_{i=1}^{m} w_i \phi_i(\mathbf{x}) + w_0$.

With respect to this signal de-noising formulation our method consists of the following steps, where the aim of the function $f(\mathbf{x})$ is signal recovery from the original noisy measurement:

1. inputs ($\mathbf{x}$) are equidistantly sampled points in input space; in 1-D we pre-define sampling interval to be $[-1, 1]$ and the number of sampling points then depends on the selected sampling rate. This allows us to find optimal or near optimal parameters for the kernel mapping (or even particular kernel mapping) for different classes of signals under investigation.

2. the basis function $\phi_i(\mathbf{x})$ are taken to be components obtain by KPLS, which may be seen as the estimates of an orthogonal basis in a feature space defined by the kernel function used. These estimates are sequentially obtained using the existing correlations between nonlinearly mapped input data and the measured noisy signal [1].

3. to set the number of basis functions m we have used the VC-based model selection criterion described in [2]. The ordering of the basis functions for the purposes of the used model selection criterion is defined by their sequential extraction.

4. using the locally based KPLS allows us to deal with a possible discontinuity and non-stationarity in the signal of interest. Locality is achieved using modified KPLS algorithm incorporating the weight functions that reflect the local areas of interest. Depending on weight function selection this allows us to construct soft or hard thresholding regions where KPLS is constructed. The final estimate is composed of individual local KPLS models.

We extensively compared our method with carefully optimized wavelet de-noising using heavisine and artificially generated brain event-related potentials (ERP) distributed over individual scalp areas. We varied the levels of additive white or colored noises added to the clean signals. Using the KPLS method we observed consistent improvement in the terms of noise reduction especially in the situations of lower signal-to-noise ratios (SNR $\leq$ 5dB) and where less than 1000 sampling points were available.

Our ongoing experiments are testing different strategies for model selection and weighting functions with the goal of automatic de-noising for various classes of signals. One particular focus is on the detection of single-trial event-related potentials for application to brain-computer interface development [3]. These results will be also presented.

References

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